

Multi-subject spatial filtering in brain-computer interfaces

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I. INTRODUCTION

Brain-computer interfaces (BCI) present new communication alternatives for severely disabled people. Although these BCI systems exist in many flavors, the system we focus on is based on the imagination of hand and/or foot movements. The interface then tries to detect the correct imagined movement from the subject's brain signals. These kind of systems commonly use the common spatial pattern filter (CSP) as preprocessing step before features are extracted from the EEG signals and classified as one of the mental movement tasks (also referred to as classes). The CSP method is a supervised algorithm and therefore needs subject specific training data for calibration, which is very time consuming to collect. Instead of letting all that data and effort go to waste, we could use the data of other subjects to further improve the BCI performance for new subjects. This problem setting is often encountered in multitask learning, from which we borrow some ideas and apply it to the preprocessing phase.

II. APPLIED METHOD

The goal of the basic CSP method, proposed by Müller-Gerking in [1], is to learn a spatial filter for *one* subject that maximizes the signal variance for trials of one class while at the same time minimizes the signal variance for trials of the other classes. This results in features which are optimal for classification. The spatial filter \mathbf{w} is nothing more than a linear com-

Table 1. Accuracy obtained on the test sets of five subjects of the third BCI competition, comparing the basic bCSP method with its multi-subject variant msCSP.

method \ subject	<i>aa</i>	<i>al</i>	<i>av</i>	<i>aw</i>	<i>ay</i>
bCSP	68.33	95.56	56.67	63.89	90.00
msCSP	64.44	95.56	67.78	73.89	90.00

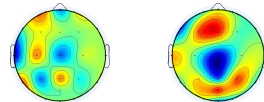


Figure 1. *Left* shows a subject specific filter for subject *av*. *Right* shows the more neurophysiologically plausible global filter.

bination of the incoming brain signals. We extend this approach by splitting the spatial filter $\mathbf{w}_s = \mathbf{w}_0 + \mathbf{v}_s$ into two components. The first one being a global filter \mathbf{w}_0 , computed on data of all subjects, and the second one a subject specific filter \mathbf{v}_s for each subject s .

III. RESULTS AND CONCLUSION

In Table 1, one can clearly see that some subjects (*av* and *aw*) display a significant increase in performance by using information of other subjects (see also Figure 1 for the difference between the two type of filters), while in some subjects the algorithm determines that a specific filter is the best (*al* and *ay*). In the future, a fully global filter could be constructed to alleviate the need for collecting a lot of calibration data.

REFERENCES

- [1] J. Müller-Gerking, G. Pfurtscheller, and H. Flyvbjerg, "Designing optimal spatial filters for single-trial eeg classification in a movement task," *Clinical Neurophysiology*, vol. 110, no. 5, pp. 787–798, 1999.

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